“J”-shaped returns to timing advantage in access to information – Experimental evidence and a tentative explanation[#]

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Abstract

The question of how useful information is in financial markets has been discussed for decades and is still unresolved. In this paper we challenge the widely held belief that additional information is never a disadvantage. We present results from experimental financial markets with asymmetrically informed traders. In all treatments we conduct we find a “J”-shaped distribution of returns: while the best informed outperform all others, average informed traders have significantly lower returns than the least informed. This can mainly be attributed to trend reversals in the fundamental information. Prices in our markets do not reflect REE, but rather ‘naïve trader’ equilibrium.

JEL-classification: C91; D82; D83 ; G10

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1 Introduction

In 1970 Fama published his seminal paper “Efficient Capital Markets,” provoking practitioners and many theorists with the thesis that gathering information is useless in efficient markets, as all information is already reflected in prices. However, with the information paradox Grossman (1976) and Grossman/Stiglitz (1980) showed that strong form efficient markets are not possible and that gathering information makes sense up to the point where its marginal cost equals its marginal benefit. In an experimental study Sunder (1992) found evidence supporting this. In this paper we agree with this, but we offer another provocative thesis: our experimental data suggest that apart from its cost, information can lower the expected return of an investor. This experimental result is supported by empirical findings from the past seven decades.

The statement “the more information, the better” is generally accepted as it seems intuitively obvious. The most frequently cited reference in this respect in economics is probably Blackwell (1951, 1953). However, the widespread belief that having more information is always better (or at least never worse) in financial markets is surprising, given that researchers in many different disciplines have shown that more public or private information is not always better for those who use it. Especially game theoretical models teach us that more information may harm some or even all agents. Almost 60 years ago von Neumann and Morgenstern (1947) argued that a player may find it advantageous to forego some information. Savage (1954) lists several cases where information can be disadvantageous for psychological reasons or because it makes bets impossible. Hirshleifer (1971) shows that public information in markets with risk-averse individuals can make them worse off as it may destroy insurance opportunities that would have been available without the public information. Gersbach (2000a, 2000b) shows that the value of public information in social choice situations may be negative for a majority of voters. Even in disciplines like supply chain management, models show that information can be harmful, as e.g. in Iyer et al.

(2005). In a good overview Bassan et al. (1997) present several game theoretical settings where information can be advantageous to both players, disadvantageous to both, or advantageous to one and disadvantageous to the other – depending on the specific setting. Their main message is that "*in an interactive decision framework with incomplete information, the relevant issue is that of interactive knowledge rather than simply knowledge per se*." (Bassan et al. 1997, 3). We think this is also true on financial markets.

For us, the game-theoretical approaches are especially interesting, as we understand the market as a strategic game where investors try to outsmart each other. We think that Gibbons' (1992, 63) conclusion that in game theory "*having more information … can make a player worse off*" also holds true for financial markets. Schredelseker (1984) claims that information may be harmful for traders in a market context. He argues that an uninformed trader can only choose stocks randomly, earning on average the market return when he is a price-taker. If insiders are able to outperform the market, some traders (the average informed) have to receive returns below the market return.[1]

In the empirical field Cowles was the first to raise doubts about the usefulness of information processing in financial markets as early as 1933. The abstract of his paper "Can Stock Market Forecasters Forecast?" had just three words: "*It is doubtful*." He conducted an extensive study of how well four different groups of stock market forecasters performed relative to the whole market. None did better than could be expected by pure chance, and simple random strategies outperformed the practitioners – as did the broad market (Cowles 1933). These results were confirmed by a second study covering more than 15 years of forecasts (Cowles 1944).

[1] Schredelseker (2001) shows in a binomial setting that information is harmful to the average informed only if all traders actively use their information. However, if traders can learn and switch strategies they will do so until a situation is reached, where information is just useless but not harmful. We found the same result in earlier experiments (Huber et al. 2006a, 2006b).

Two decades later Jensen (1965) examined the performance of mutual funds compared to a broadly diversified market portfolio. Only 26 of the 115 funds covered in the study performed better than the market, and on average they fared 15 percent worse than the market over a period of ten years. Jensen, surprised by these results, wrote, "*One must realize that these analysts are extremely well endowed. Moreover, they operate in the securities markets every day and have wide-ranging contacts and associations in both business and financial communities*." If they cannot beat the market, how can a small investor taking advice from his bank or some stock market newsletter expect to?

Malkiel presented similar results in several studies (e.g. Malkiel 1995, 2003a, 2003b). In two recent papers (Malkiel 2003a, 2003b) he criticized the underperformance of professional investment funds compared to the index: on average, the market outperformed more than 70 percent of actively managed stock market funds over a ten-year period, and the figure for bonds is even worse at 90 percent. Nevertheless the dominant belief in our discipline is still that information is the most important ingredient to achieve above-average returns. This belief persists even though empirical, theoretical and experimental studies suggest that the matter is not that simple.

With this paper we want to offer an explanation for why average informed traders may perform worse than the least informed in financial markets. Our study suggests that their poor performance is due not to mistakes they make or faulty information; it can be attributed to the effect of trend reversals on the distribution of returns among asymmetrically informed traders. This will be shown by results from several experimental financial markets.

The paper is organized as follows: after the introduction we present our market model in section 2. Section 3 covers the experimental implementation, and section 4 presents equilibrium predictions. Section 5 presents results from the experiment and section 6 concludes the paper.

2 Market model and experimental implementation

In the past thirty years several authors (e.g. Grossman/Stiglitz 1980, Hellwig 1982, Figlewski 1982, Kyle 1985, Copeland/Friedman 1992, Ackert et al. 2002) have developed models with asymmetrically informed traders. However, all these models are limited to only two information levels: "uninformed" and "informed". We present a model with more than two information levels. This is not only a quantitative, but also a qualitative change: with just two information levels, it is no surprise that the informed will never perform worse than the uninformed. With three or more information levels, though, strategic thinking starts to play a more important role: now we have a market with several asymmetrically informed agents who try to outsmart each other.

We set up a multi-period model where asymmetrically informed human subjects trade a risky asset. The core of our model and its key innovation is the information system which provides traders with information about the fundamental value of the stock. We conducted three different treatments (T1, T2, and T3). We will first explain the setting for T3, and then turn to T1 and T2. While T3 was the last treatment to be conducted, it is the easiest to explain.

To implement an asymmetrical information structure with several information levels, we start with Hellwig`s (1982) idea that better informed traders have an information advantage because they get relevant information earlier than others. We extend this concept to five information levels *I1* to *I5,* with (5-*x*) in *Ix* specifying how many periods later than the best informed (*I5*) the fundamental value becomes available to a specific information level. This means that the information provided to *I5* in period t becomes available to *I4* in period t+1, to *I3* in period t+2, etc. Like a hot potato, information is passed on from one investor to the next each period, leaving enough time to place orders and make trading decisions in between.

The fundamental value in T3 is a random walk process generated by geometric Brownian motion:

$$CPV_t = CPV_{t-1} * e^x \tag{1}$$

with CPV_t representing the fundamental value at time t and x being a normally distributed random variable with mean 0.5% and standard deviation 7.2%. Traders are informed about this process in the instructions and we tell them that the random numbers are generated by the computer.

This design results in information trickling down through the market from the best informed to the broad public over time. Even the least informed traders *I1* get the same fundamental information as *I5* – only four periods later than insiders do. For the sake of simplicity we assume that traders know the exact fundamental value and they never get wrong information. At the beginning of each session in all three treatments, each trader is randomly assigned to an information level and then keeps this level for the whole session. The asymmetric information structure is common knowledge in the experiment, i.e. traders know that there are four traders (two traders in T3) for each of five information levels, they know their own information level and they know that this information level will not change throughout the experiment. At the start of each period, each trader gets new information on the fundamental value formerly only known to the next best informed (or to nobody in the case of *I5*). Then participants can trade in a continuous double auction market for 100 seconds until the period ends. As on most stock exchanges all orders are executed according to price and then time priority. Market orders have priority over limit orders in the order book. This means market orders are always executed instantaneously. In all three treatments holdings of money and stock are carried over from one period to the next.

In T3 the stock does not pay dividends and no interest is paid for money holdings. The termination value of the stock is the fundamental value (information provided to *I5*) in the last period. In this treatment going short in money and stocks is possible without limitations. This is an important difference to treatments 1 and 2 where shorting money or stock is not possible. This brings us to the slightly more complicated treatments T1 and T2. In these treatments the information structure is very similar to the one in T3, but the fundamental value (called "conditional present value", CPV) of the stock is based on future dividends which are paid at the end or each period. Again we have five information levels (*I1* to *I5*), with *x* in *Ix* specifying the number of future dividends known to a trader. Traders with information level *I1* know the dividend for this period, traders *I2* know the dividends for this period and the next, and so on up to the best informed ("insider") *I5*, who knows the dividends for this and the next four periods. Figure 1 illustrates how far each information level can forecast future dividends.

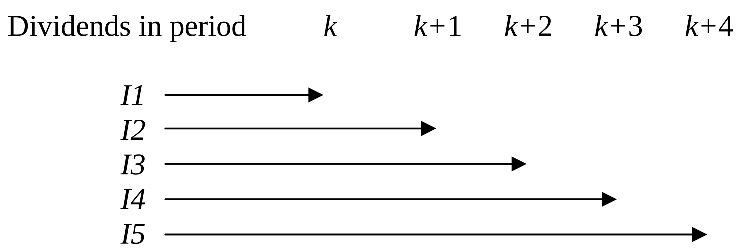

Figure 1: Overview of traders' knowledge about future dividends

With this construction we get a market with an asymmetric information structure where better informed traders always know future dividends earlier than worse informed ones. Traders *I5* are always the best informed in the markets presented here, but with this setting a market can easily be implemented with any desired number of information levels.

At the end of each period in T1 and T2, the current dividend is paid out and a known risk-free rate is paid for cash holdings. At the start of the next period, each trader receives new information previously known only to the next-best-informed trader – or that is completely unknown in the case of *I5*. This means that the former dividend for period (k+1) is the dividend for period k one period later. As in T3 the informational advantage of better informed traders is one of time. The underlying dividend process in T1 and T2 was designed as a random walk process without drift:

$$D_k = D_{k-1} + \varepsilon \qquad (2)$$

D_k represents the dividend in period k and ε is normally distributed with $N(0;\sigma^2)$ with a standard deviation of 0.12. The starting dividend D_0 = 0.8. Again traders were informed that the random numbers are generated by the computer.

3 Experimental treatments

In this section we describe some details of the three treatments we implemented. In all three treatments each trader has a starting endowment of 1,600 talers (experimental currency) and 40 shares of a virtual company. In T1 and T2 the companies' dividends are derived using the process of equation (2), in T3 the fundamental value follows the random walk of equation (1). In our experiment information is provided for free, i.e. there are no information costs.

The trading mechanism is a continuous double auction with an open order book where traders can freely post limit orders or place market orders for 1 to 10 stocks. Market orders are only allowed under the condition that there is at least one limit order in the order book. Partial execution of limit orders is also possible. There are no transaction costs and we set practically no limitations on trading, meaning that traders can buy or sell as much as they want at any price within the range [0:200]. In T1 and T2 short selling or buying on credit is not allowed, however, in T3 these restrictions are lifted and traders can go short in money and stocks.

At the start of each session traders are briefed with written instructions,[2] which take about 15 minutes to go through. After this introduction we run four trial periods to allow participants to become familiar with the trading screen. We then start the main experiment lasting about 40 to 45 minutes Trading is randomly terminated between periods 20 and 30 (each period lasting 100 seconds) with equal probability for each period.[3]

[2] See experimental instructions in Appendix A.

[3] This was also told to participants in T3. However, all markets were terminated after period 24. In market 2 of T3 the data for the last period was not saved so we have only data for 23 periods for this market.

In T1 and T2 participants get information on future dividends which are then discounted to the present. The risk-free interest rate r_f for cash holdings is set at 0.5% per period; the risk adjusted interest rate r_e for discounting future cash flows (dividends) and therefore the average dividend yield is 2.0% per period.[4] In addition to dividend information we provide each trader with the conditional present value of the stock ($CPV_{j,k}$) on the basis of the given information (see screenshot in Appendix A). This is calculated using Gordon's formula, discounting the known dividends and assuming the last one as an infinite stream which is also discounted. $CPV_{j,k}$ stands for the conditional present value of the asset in period k, j represents the index for the information level of the trader, and r_e is the risk-adjusted interest rate.

$$CPV_{j,k} = \sum_{i=k}^{k+j-2} \frac{D_i}{(1+r_e)^{i-k}} + \frac{D_{k+j-1}}{(1+r_e)^{j-2} \cdot r_e} \tag{3}$$

The resulting paths of CPVs of the asset for all five information levels in each market are plotted in Appendix B. Beginning with *I5*, the functions are shifted to the right for each information level *Ij* by (5-*j*) periods, reflecting that better informed participants receive information earlier than worse informed ones. For the five sessions of T1 five dividend processes were generated using equation (2). To make the results of the first two treatments easily comparable we took exactly the same dividend processes to run the five sessions of T2. All other variables were also identical in T1 and T2 to clearly see which influence the means of presenting information has. In these two treatments each market is implemented with 20

[4] As we tell participants that periods represent quarters of a year, the respective risk-free and risk adjusted interest rates are 2.01 and 8.24 percent p.a. We provided traders with the CPV based on r_e and dividends, as almost all our participants were business students who knew what a dividend discount model is. They learn how to calculate the present value of finite and infinite future cash flows in their first year, so we decided to build on that knowledge instead of just providing a "fundamental value". We used the same r_e for all participants, as everything else would have been even more arbitrary. When asked, participants confirmed that they understood the design. In T3 there are no longer dividends and discount rates, so only the traders' information on the intrinsic value is shown on the screen.

traders. Four traders are randomly assigned to each of the five information levels. At the end of each session traders are paid in real cash according to their performance in the market relative to the market average.[5]

In T3 no interest or dividend is paid and we do not need a formula to calculate CPV as this is derived following equation (1). In T3 we ran six markets with ten traders each. At the start of the session two traders were randomly assigned to each information level and then retained this information level for the whole session. At the end of the session all stocks were bought back at the fundamental value (CPV of *I5*) and traders were paid according to their final wealth (value of their stocks plus money holdings). There is no benchmarking to the performance of others as in T1 and T2.

In all three treatments participants always get current information about their cash and stock holdings, their wealth, and their transactions within the current period. In the center of the screen they see the open order books and they have the opportunity to post limit of market orders.[6]

The first two treatments (T1 and T2) are mainly distinguished by the way information on prices is presented to participants (tables in T1 vs. charts in T2). In addition in T1 CPV is displayed prominently on the lower left side below dividends. On the right side tables with a chronological price history of the current period (lower right side), and the mean price of all previous periods (upper right side) are displayed.

[5] This incentive structure can be considered a tournament, which has been criticised e.g. by James/Isaac (2000) for its potential to lead to misleading prices. However, the same authors mention that mutual funds managers are usually paid in this way (depending how much they “beat the market”), and that these funds increasingly dominate the market. This is the main reason we chose this incentive structure in T1 and T2. However, in T3 we chose a straightforward structure where traders receive the final value of the stocks they hold plus their cash.

[6] See screenshots in Appendix A.

In T2 the information system is more sophisticated and visual presentation is more important. CPV is now less prominent, as it appears in a small box below current wealth. Below CPV the current price is displayed in the same design and size. Information on the development of prices is now displayed in a chart depicting all transaction prices with the respective time. This chart dominates the left-hand side of the screen. After each transaction the chart is immediately updated. The right side of the screen is kept blank in T2, as the information on past periods is presented in a separate history screen which is shown for 10 seconds after each trading period. This gives participants time to look at longer-term developments. On this history screen traders get more information than they got in T1. Separated for each period, they see a table with their own stock and cash holdings at the end of the period, the last transaction price, their resulting wealth, their own and market trading volume, and the dividend paid. In addition a chart displaying the average prices of all past periods is shown. In T3 we use the same trading and history screens as in T2, with the only change being that no dividends are displayed, as there are no dividends in T3.

We conducted five sessions each for T1 (in January and February 2005) and T2 (in January 2006) at the University of Innsbruck with a total of 200 business students. T3 was conducted with 60 students at Yale University in July 2006. Most participants had taken part in other experiments in economics, but none participated in more than one of the markets in this experimental series. Each session lasted about 80 to 90 minutes, and students were paid an average of 16 euros in T1, 19 euros in T2, and 22 US-$ in T3. The experiment was programmed and conducted with z-Tree (Fischbacher 1999).

The following table gives an overview of the stages of the experiment. The sequences for the three treatments are identical with the exception of step 5.IV (history screen), which appears only in T2 and T3, but not in T1.

Table 1: Sequence of steps in the experimental treatments

1)	Participants are randomly assigned to different information levels (they do not yet know anything about the experiment and they do not know their information level)
2)	Written instruction is read out loud and questions are answered privately (~15 minutes)
3)	Participants learn their information level on a separate screen
4)	Four trial periods allow participants to get accustomed to the trading mechanism (each period features the steps described below in the main periods, ~7 minutes)
5)	Everything is reset (same starting endowment, etc.), last opportunity to ask questions
6)	Start of the experiment (20 to 30 periods). Each period lasts 100 seconds and includes the following steps:
	I. Order books, boxes displaying own transactions in this period, and price history (T1) or chart (T2 and T3) are emptied. New information on dividends and resulting CPV (only CPV in T3) is displayed to each participant
	II. Trading starts; participants can freely place limit orders or accept limit orders from other traders (this equals a market order) for 100 seconds. Theoretically an unlimited number of orders is possible, conditional on having enough cash (for bids) and stocks (for asks) to execute the posted orders in T1 and T2. There are no limitations in T3. Resulting transactions are immediately settled at the respective price. Prices therefore vary within a period. Stock and cash holdings, prices, wealth, as well as the table displaying past prices (only in T1), and the chart (in T2 and T3) are immediately updated on the screen of each participant
	III. At the end of the period (after 100 seconds) dividends are paid out for each share held and the risk-free rate is paid for current cash holdings in T1 and T2
	IV. A history screen showing stock and cash holdings, wealth, closing price, own and market trading volume, the paid dividend, and a chart displaying the average prices of all past periods is shown for 10 seconds (only in T2 and T3)
	This sequence (I to IV) is repeated until trading is terminated. This happens randomly between periods 20 and 30 with equal probability
7)	Short questionnaire on demographic data (2 minutes)
8)	Payout to participants in real cash

4 Equilibrium predictions

Given that the information structure is common knowledge, traders with information level *I1* know that all their counterparts (except the other *I1* traders) are better informed. Given this knowledge of their informational disadvantage, entering into transactions is not rational, and they should adopt a buy-and-hold strategy to earn the market return, i.e. they should refrain from trading and keep their initial endowment. This line of argument can be extended to the traders with information level *I2*: given that rational traders *I1* do not trade, *I2*s are the worst informed among the active traders, and can only expect to lose in transactions with other, better informed traders. Consequently, *I2* traders should also abstain from active trading. Extending this line of thinking to *I3* and *I4* leads to a market where only traders with information level *I5* are active. In a market which is effectively populated only by fully informed traders, prices should provide a fully revealing rational expectations equilibrium (REE), and the number of transactions should be small. Different liquidity or risk-preference among the *I5* traders would be the only incentive for transactions in such a market. Barring collusion or coordinated action (which is unlikely as participants are selected and seated randomly, information levels are assigned randomly and communication is not possible) which might create a bubble, this situation replicates something close to a no-trade situation. If REE holds, the return distribution across information levels will be flat, as all traders start with the same endowments and receive the market return for it.

As alternative to REE we propose what we call ‘naïve trading’ (other names have been used, e.g. ‘prior information equilibrium’ in Plott/Sunder, 1982), which assumes that traders are not aware of – or ignore – the strategic implications of the known information structure. If traders act on the basis of their respective private information, heterogeneity of fundamental information provided will lead to very active trading. This would require all traders, except the *I5* traders, to behave as if they did not know or care that they are competing against traders who have better information. The resulting price paths are different from REE predictions. If we assume all traders to be approximately equally active, and if they base their trading decisions on the fundamental information provided to them, those with the highest estimate about the value of the stock will buy, while those with the lowest will sell. Consequently prices will be between the highest and the lowest fundamental estimate (CPV). When all traders use the fundamental information provided in a market with five information levels, each period the two with the highest CPVs will predominantly buy from the two with the lowest CPVs. The equilibrium price in each period will be the median CPV (the third highest CPV in a respective period), as that is the point where supply and demand curves intersect.

In a seminal paper, Smith (1982) showed that prices in a double auction market quickly reflect the intersection of supply and demand curves. However, his analysis applies to a static environment where equilibration is easier to achieve than in our dynamic setting. The relation only holds if all traders use the information they get and if all are equally active. If traders use 'naïve trading' the return distribution will show differences between information levels, as insiders will profit from their informational advantage at the expense of less informed traders.

5 Results

As similarities between the three treatments outweigh differences we will present results for all three treatments together and highlight differences where appropriate.

5.1 Trading activity

We observed very active trading in all our markets, with on average around 900 transactions per market in T1 and T2 and 463 transactions per market in T3.[7] The lower

[7] Each transaction can be for one to ten shares. A trade for exchanging one share is one transaction, as is a deal where traders exchange any number up to ten shares. The number of transactions can be higher than the number of posted orders, as one order for 10 shares can lead to up to ten transactions (of one share each).

number for T3 is simply a consequence of the lower number of traders in these markets. Per trader the averages are comparable. The number of stocks traded and orders placed per trader is roughly comparable in all three treatments.

Table 2: Overview data for treatment 1 (top), treatment 2 (middle), and treatment 3 (bottom)

T1	# of traders	# of periods	# of shares traded	# of transactions	Avg. # of shares per transaction	# of orders placed	Avg. mean price	Std.dev. prices/ period
M1	20	25	1872	354	5.29	804	40.18	0.99
M2	20	25	3118	652	4.78	1107	45.42	2.07
M3	20	24	3781	1067	3.54	1346	36.99	1.96
M4	20	26	4551	1224	3.72	1564	38.18	1.97
M5	20	27	3231	1168	2.77	1389	39.35	1.00
Average			3311	893	3.71	1242	40.02	1.60

T2	# of traders	# of periods	# of shares traded	# of transactions	Avg. # of shares per transaction	# of orders placed	Avg. mean price	Std.dev. prices/ period
M1	20	25	4349	997	4.36	1558	41.77	0.47
M2	20	25	2781	805	3.45	1288	41.48	0.81
M3	20	24	4107	726	5.66	1201	37.97	0.50
M4	20	26	3462	1200	2.89	1365	38.15	0.74
M5	20	27	3553	813	4.37	1630	39.87	0.57
Average			3650	932	3.92	1353	39.38	0.62

T3	# of traders	# of periods	# of shares traded	# of transactions	Avg. # of shares per transaction	# of orders placed	Avg. mean price	Std.dev. prices/ period
M1	10	24	1382	346	3.99	691	43.38	0.66
M2	10	23	1255	352	3.57	267	41.08	1.42
M3	10	24	2537	513	4.95	974	45.83	0.65
M4	10	24	3674	1068	3.44	835	37.81	2.12
M5	10	24	877	238	3.68	233	54.53	0.47
M6	10	24	747	260	2.87	672	39.32	0.71
Average		24	1745	463	3.75	612	43.66	1.00

While levels of trading activity varied widely across individual traders, none was completely inactive.[8] We also saw no breakdown of any market as REE and several no-trade theorems suggest for markets with asymmetric information (e.g. Fudenberg/Tirole 1991, Lucas 1978, Judd et al. 2003). The number of posted orders per trader and period did not change significantly over time and ranged from 2.4 to 3.0 in all three treatments. Obviously

[8] The number of transactions ranged from 8 to 323 for individual traders, with an average of 89 in T1, 3 to 260 with an average of 93 in T2, and 6 to 487 with an average of 92 in T3.

the injection of new information to each trader each period and the resulting variation in expectations stimulated very active trading throughout the whole experimental session. This is in line with our 'naïve traders' prediction, but not with REE.

In T1 the number of transactions decreased from an average of 4.2 per trader and period in the first eight periods to an average of 3.1 in periods 17 to 24. We also see (smaller) decreases in T2 (from 3.9 to 3.5) and T3 (from 4.0 to 3.9; the changes in the first two treatments are significant, in T3 it is not; two-sided Mann-Whitney U-test p=0.001 in T1, p=0.040 in T2, and p=0.833 in T3). In all three treatments we see the highest or second-highest number of transactions in the first period, as traders adjust portfolios to their preferences and expectation. We attribute the decrease mainly to learning (to wait for better offers) and probably also to tiring after some time of trading. In addition we found several traders who sold all their shares in the beginning and then traded (almost) nothing for the remainder of the experiment. These traders' activities contribute to high numbers of transactions in the beginning and lower numbers in later periods.

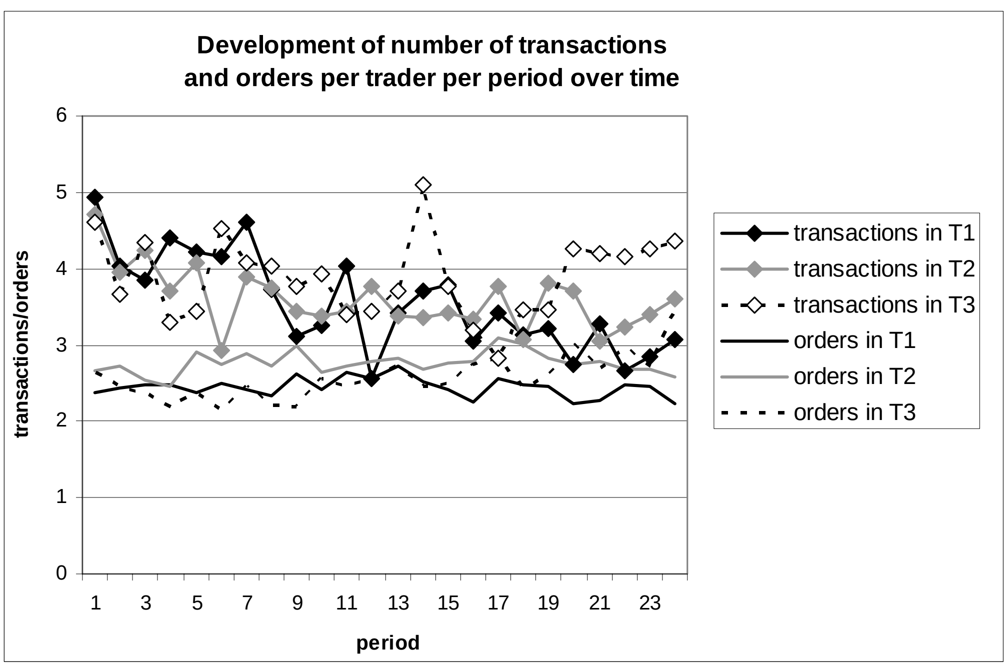

Figure 2: Development of trading activity over time: number of posted orders and number of transactions per trader and period in treatment 1(T1), treatment 2 (T2), and treatment 3 (T3)

When we look at the overall activity of different information levels we find no significant differences. The average number of transactions per trader throughout the session range from 73 to 105 in T1, from 77 to 108 in T2, and from 83 to 97 in T3 for different information levels (p-values of two-sided Mann Whitney U-tests when we compare individual levels with all others are 0.2 and above). Again, this result is not in line with REE, as all traders who have no insiders information should refrain from trading in equilibrium, but it is in line with 'naïve trading' predictions.

5.2 Information and return

To compare the performance of traders and information levels across markets, we computed the average final wealth in each market and compared each trader's wealth with the average of his market. A net return of zero is therefore the benchmark or market return. Figure 3 shows the results for each individual trader (diamonds) and the average for each information level (solid line).

We see that information does matter, as we find significant differences between the information levels. There is clearly no monotonic relationship, as traders *I1* with a net return close to zero are more successfully than the better informed traders *I2* and *I3* in all three treatments. The resulting functions of net return show a "J"-shape. As expected, the best informed *I4* and *I5* are able to outperform the market in all three treatments with average net returns significantly higher than zero for *I4* and *I5* in T1 and *I5* in T2 and T3.[9] We see the highest magnitude of net returns in T3. As will be explored later this is mainly caused by the possibility to go short in stocks and money in this treatment.

[9] Significantly different from zero at the 10 percent level, two-sided Mann Whitney U-test, N=5 in T1 and T2, N=6 in T3. If we test for individual traders instead of aggregated data for information levels, the results for *I5* are significant at the 1 percent level in all three treatments.

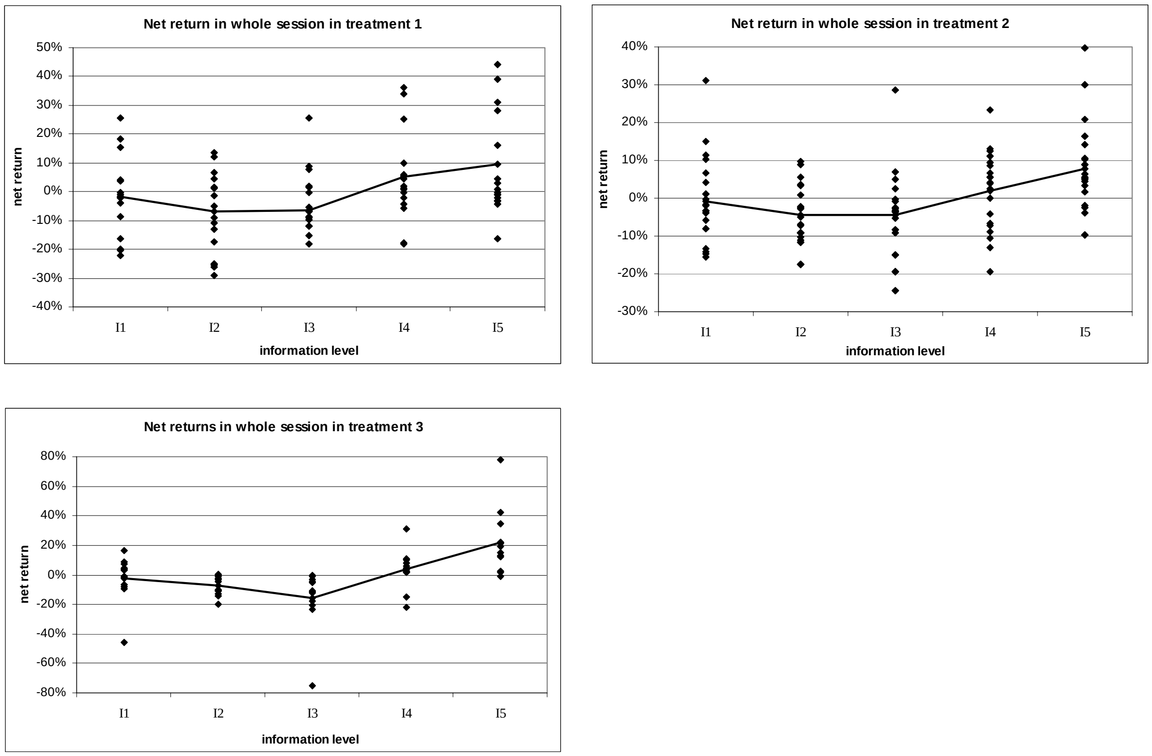

Figure 3: Relationship between information level and net return

in T1 (top left), T2 (top right), and T3 (bottom left)

The statistical comparison of net returns of different information levels confirms the findings from figure 3: in all three treatments *I5* performs significantly better than *I1*, *I2* and *I3*. For the second-best informed *I4*, we find similar significances in T1 and T3, but not in T2. This confirms that the best informed are able to outperform other traders, as many earlier studies have shown. While there is no significant difference in the returns of *I2* and *I3* in any treatment, it is remarkable that the worst informed *I1* perform significantly better than *I2* and *I3* in the first two treatments and better than *I3* in the third treatment. In our markets insiders outperform all other traders, while the worst informed have significantly higher returns than the average informed *I2* and *I3*. This result is in line with 'naïve trader' expectations, but not with REE, where all traders should have the same net return.

Table 3: p-values of paired two-sided Wilcoxon-signed ranks tests (N=5) on differences in net returns between information levels (N=5)

T1	I1	I2	I3	I4
I2	0.04**			
I3	0.08*	0.89		
I4	0.04**	0.04**	0.08*	
I5	0.04**	0.08*	0.04**	0.89

T2	I1	I2	I3	I4
I2	0.08*			
I3	0.08*	0.89		
I4	0.50	0.50	0.23	
I5	0.08*	0.08*	0.04**	0.23

T3	I1	I2	I3	I4
I2	0.46			
I3	0.05**	0.35		
I4	0.60	0.03**	0.03**	
I5	0.05**	0.03**	0.03**	0.05*

* significant at the 10 percent level
** significant at the 5 percent level

Our result is in no way due to wrong information or the cost of information: all information in our experiment is provided for free and is always correct. If information costs were included, the returns for average and high information level would decrease most, stressing even more the good performance of the worst informed.

When looking for factors distinguishing successful from unsuccessful traders within information levels we explored the number and time of transactions and number and time of orders posted. The only factor where we found significant differences was the number of orders posted. Successful traders post significantly more orders than unsuccessful ones in T1 and T3. Rather than accepting limit orders from other traders the most successful traders set limit orders and wait for others to accept them, thereby avoiding to pay the bid-ask spread.

5.3 A tentative explanation for the distribution of returns

We think the distribution of returns we observe can be explained by looking at what happens in two distinct phases of a price path. Basically, there are only two ways a price path can develop over time: either the sign of the price change is the same for several consecutive periods (a ‘trend’), or the sign of the price change alternates frequently (typical for a ‘trend reversal’). This simple distinction is crucial for our analysis, as we will see that the distribution of returns is different in the two situations.

When a trend, i.e. a sustained series of subsequent upward or downward movements, begins, it is undoubtedly advantageous to know about it as early as possible. In the case of an upward trend, a well informed trader can buy while prices are still low, while worse informed buy later at higher prices, and vice versa for a negative trend where insiders start selling first. Figure 4 shows an upward trend for a market with five information levels. We also display the median CPV (here always *I3*) as we will see below that this is a good proxy for the development of prices in our markets, as suggested by the 'naïve trader' equilibrium.

During a trend as displayed in figure 4 insiders will buy at still-low prices from worse informed traders who have lower CPVs. If we would assign ranks to the CPVs from rank 1 (highest) to rank 5 (lowest), the ranks would not change from one period to the next during a trend. In situations like this, being better informed is never a disadvantage.

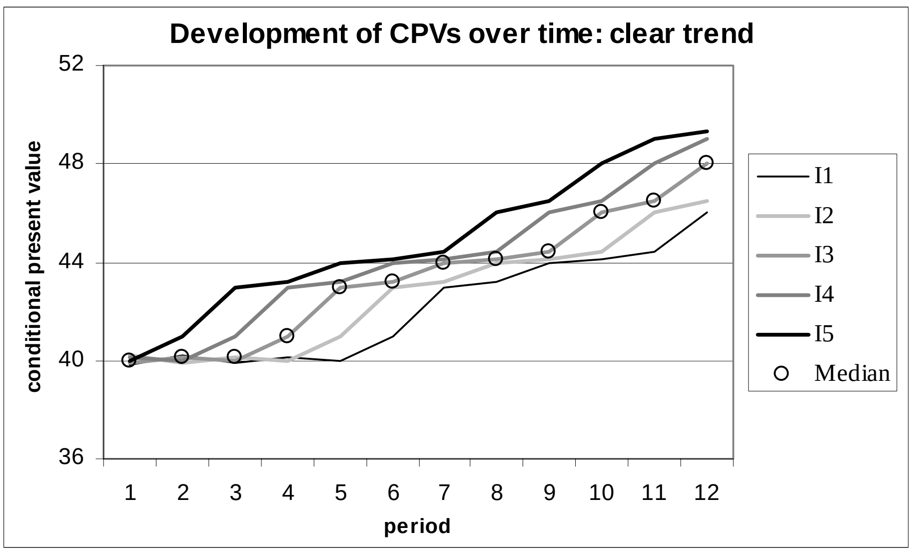

Figure 4: Development of conditional present values (CPVs) during an upward trend

The second possibility in a market is the lack of a clear trend. Figure 5 presents a sequence of periods where CPVs first increase, then decrease, then rise again. This situation is more complicated to analyze, as it is more dynamic: in figure 4, *I5* always had the highest CPV, *I4* the second highest, and so on, making the average informed *I3* the median trader. Now the relative positions in the market change every few periods and if we assign ranks to the CPVs of the five information levels the ranks alternate frequently.

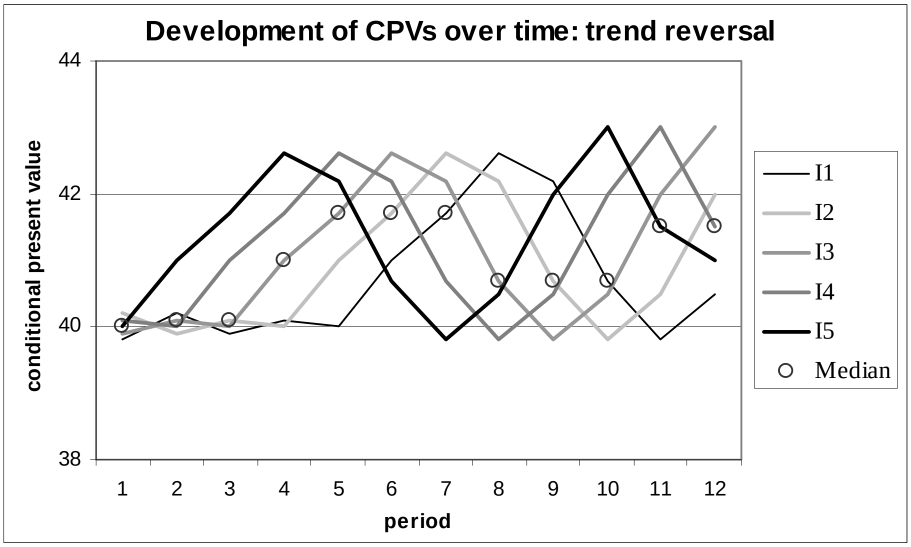

Figure 5: Development of conditional present values CPVs in a market without a clear trend

Periods 1 to 5 resemble the situation in figure 4, as we observe a clear upward trend. In the next period the situation changes dramatically: *I5* is the first to learn that the fundamental value decreases and is on the seller side in period 6, as her CPV is the lowest. While *I3* and *I4* are buying (they have estimates higher than the median) the worst informed *I1* is also selling. He does so not because he knows about a future decrease in value, but because he is not even aware of the rising CPVs ahead. In periods 5 to 7 prices (proxied by the median CPV) are highest, and in these periods the insider and the least informed sell. They see different dynamics – *I5* sees falling CPVs, while *I1* will see CPVs rising soon – but they take similar actions. Subsequently prices will fall as the median CPV decreases, and *I1* buys shares at relatively low prices in periods 8 and 9, when he has the highest expectations. *I5* also buys in periods 9 and 10 – this time *I1* is even one period ahead of the insider – again not because he knows so much, but because he knows so little. The same is true in periods 11 and 12, when *I1* is ahead of *I5* in selling shares to the average informed at high prices. This example shows that when trend reversals dominate, being worse informed is not necessarily a disadvantage.

The worst informed traders and the insiders buy low and sell high, while the average informed traders are net losers in this situation.

Our experimental data allows further investigations into whether this line of argumentation holds true in our markets. First, we can examine whether traders with relatively high (low) CPVs really bought (sold) stocks, as assumed above. Second, we should see more trade among participants with different ranks than among traders with the same rank. Finally, we can check whether the return distribution across information levels varies during trends vs. trend reversals. For the first and second analyses we rank the CPVs of the five information levels in each of the periods. The highest CPV is always assigned rank 1, the second highest rank 2, and so on until the lowest CPV representing rank 5. Note that this rank has to be distinguished from the information level. For example, *I1* would be rank 1 in a period when he has the highest of all five CPVs, but rank 2 in another, when he has the second-highest, and rank 5 in still another period when he has the lowest CPV of all five information levels.

We do this ranking for each of the total of 127 periods across the five markets in each of T1 and T2 and for the total 144 periods in the six markets in T3. Then we calculate in which fraction of all their transactions traders with the respective ranks have taken the buyer or seller position. The respective percentages are shown in figure 6.

We see that the relative rank of a trader's CPV does play an important role, as the seller share increases monotonically with rank, while the buyer share falls accordingly. The shares for traders with rank 3 are almost balanced, while traders with rank 1 were buyers in 60 to 76 percent of their transactions in the three treatments. The differences are significant on the five percent level for *I1*, *I4* and *I5* in all three treatments while the differences for *I2* and *I3* are not (two-sided Wilcoxon signed ranks test, N=5 in T1 and T2 and N=6 in T3). This result is in line with 'naïve trading' expectation, but not with REE where only traders *I5* should trade.

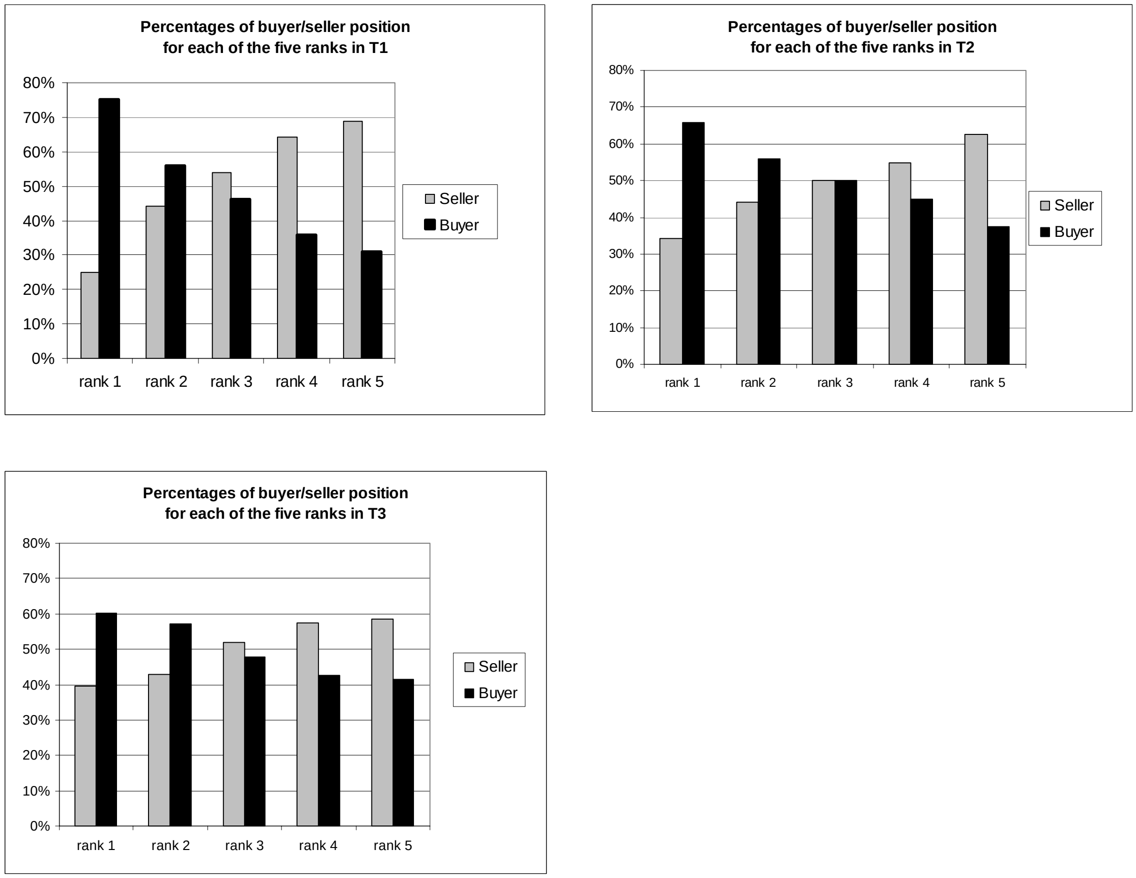

Figure 6: Percentage buyer/seller position for each of the five ranks

in T1 (top left), T2 (top right), and T3 (bottom left)

In a second step we examine which traders interacted with each other. Again we are more interested in ranks than in information levels, as e.g. *I1* and *I5* might be on the same side of the market (e.g. ranks 1 and 2) during some periods in a trend reversal, while during a trend they have very distant ranks (e.g. ranks 1 and 5). For each market we calculated how often each rank traded with each other. The respective percentages were aggregated for all markets of a treatment. We find that in each treatment transactions within the same rank are rather rare, while the frequency of trades increases with distance in ranks. The highest number of transactions is always observed between ranks 1 and 5. This is highlighted in figure 7, where we show the average share of all transactions taking place between traders with the same ranks (difference zero) up to the most distant ranks (ranks 1 and 5 with a difference of 4).

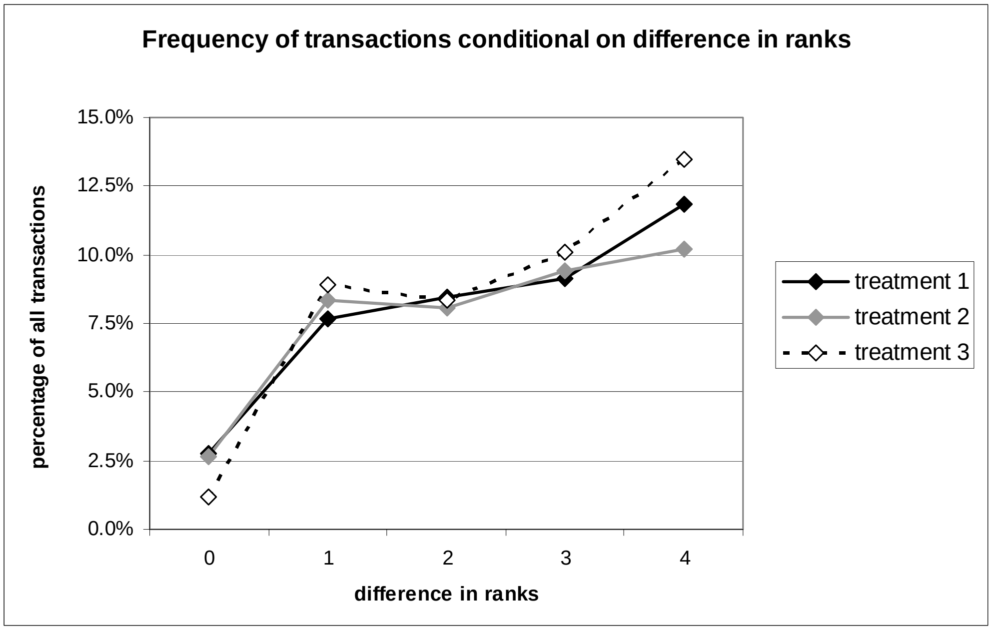

Figure 7: Frequency of transactions as share of all transactions in a market conditional on difference in ranks of the respective participants separated by treatment

In a third analysis we explore the return distribution in trends vs. trend reversals. Above we suggested that during trends additional information should never be disadvantageous, while during trend reversals being average informed may be worse than knowing less. To test whether this holds true in our markets we divide the periods in those belonging to a trend and all others and calculate each trader's return for each period. We define a trend as a sequence of periods, when average prices move into the same direction for three or more periods. A trend ends whenever prices move in another direction for at least two of four periods. Just one change within a trend is not sufficient, as we consider e.g. five subsequent price increases, then one decrease and then four more increases, a ten-period upward trend. To be able to include data for all periods we only distinguish between trends (as defined above) and all others (usually called trend reversals, as they lack a clear trend).

In T1 we find 69 periods belonging to a trend while 58 do not belong to a trend; in T2 60 periods belong to a trend, while 67 do not, and in T3 63 period belong to a trend while 75 do not. Figure 9 shows the return distributions during trends vs. trend reversals. Returns differ considerably, as during trends the worst informed (*I1* and *I2*) perform worst in all three treatments, the average informed *I3* have an average return and the best informed *I4* and *I5* earn above-average returns. In contrast during trend reversals we find *I3* with the worst return in all treatments, while *I1* always has a positive net return. While the specific numbers differ (with the highest amplitude in T3 where short selling increased the potential for profits and losses), the general pattern looks the same in all three treatments. These results corroborate the rationale outlined above.

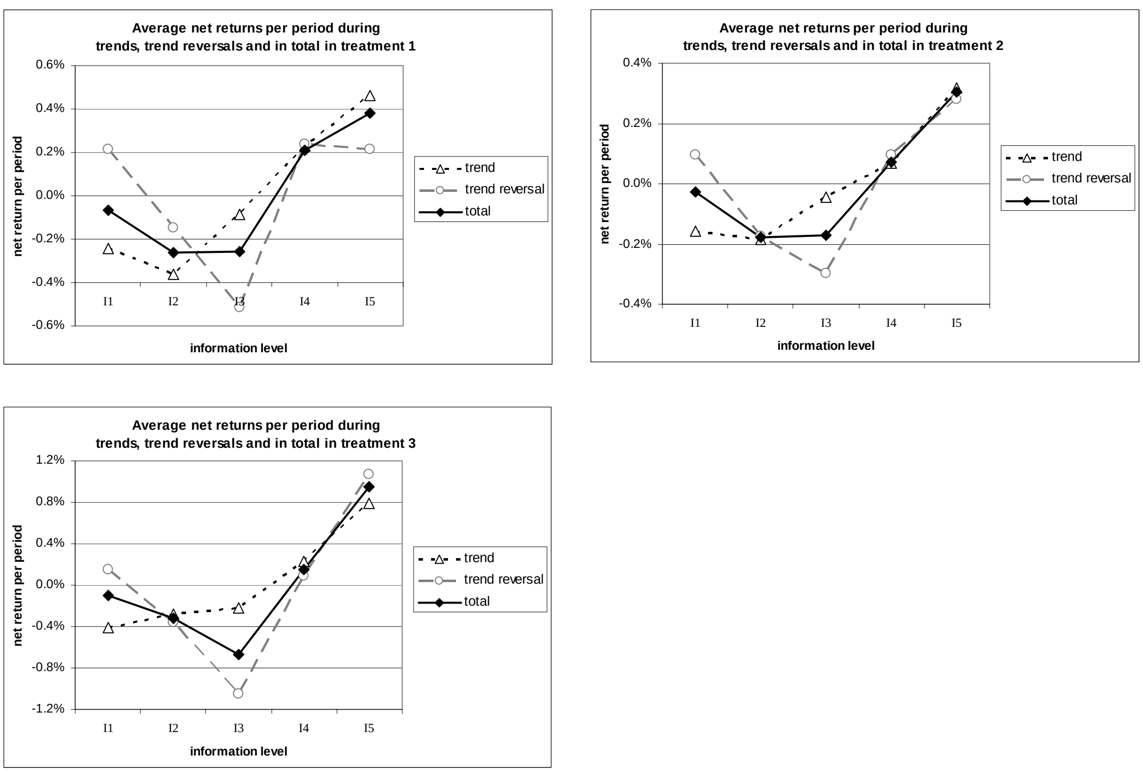

Figure 8: Net returns per period of different information levels during trends, trend reversals, and in total in treatment 1 (top left) treatment 2 (top right), and treatment 3 (bottom left)

In the literature on interacting agents, as in real world markets, we find patterns where strong trends and trend reversals alternate. In most models trends are mainly reinforced by chartists, while trend reversals happen when fundamentalists become the dominant group in a market and bring prices back to fundamentals (see e.g. Brock/Hommes 1998, Lux/Marchesi 1999, 2000, and Youssefmir/Huberman 1997). In these models and in ours information becomes more valuable, when prices deviate strongly from fundamentals.

5.4 Prices and learning

In the following analyses we present only the averages across sequences of eight periods (1-8, 9-16, and 17-24) in order not to get lost in data. This allows us to compare data for thirds of the experiment. The results for periods 25 to 27 are usually not presented as we do not have data for all markets here.[10]

When we look at the development of the standard deviation of prices within each period we see visually in the plots in Appendix B that prices within each period are becoming more stable in the last third of the experiment in most markets. Table 4 presents data on the development of prices and trading activity over time. In the first column of table 4 we see the development of the average standard deviation of prices within each period. The numbers decreases over time in all three treatments, with the changes for T1 and T2 being significant at the 1-percent level (two-sided Wilcoxon signed ranks test, N=8). We also see that standard deviation in T2 and T3 is lower than in T1 (significant on the 1 percent level for T2 and on the 5 percent level for T3, Mann-Whitney U-test). The main difference between T1 and the other two treatments was the way information on past prices was presented – namely there were charts in the last two treatments but only a list of prices in the first one. Given the vast literature on heterogeneous agent models (e.g. Brock/Hommes 1998, Hommes 2002, Kirman/Teyssière 2002, Lux 1998, Lux/Marchesi 1999, 2000) consistently demonstrating that

[10] All sessions of T3 were ended after period 24 data for period 24 in M2 lost.

the actions of chartists in markets destabilize prices, we can conclude that providing participants with charts does not make them chartists. Rather, prices became more stable, probably because past prices became more prominent and acted as a "visual anchor", while most participants probably did not take the time to look at past prices in the list in T1.

Table 4: Development of price volatility and trading activity over time and p-values for changes over periods 1-8 vs. periods 17-24 (Wilcoxon signed ranks test) in T1 (top), T2 (middle), and T3 (bottom)

T1	Standard deviation of prices/period	number of transactions per trader per period	Avg. volume per transaction	Avg. time of first trade/period	Avg. time transactions take place
Periods 1 to 8	2.48	4.24	4.23	11.3	50.9
Periods 9 to 16	1.31	3.37	4.03	10.5	52.4
Periods 17 to 24	1.08	3.05	3.82	12.8	52.3
p-value	0.00	0.00	0.12	0.16	0.34

T2	Standard deviation of prices/period	number of transactions per trader per period	Avg. volume per transaction	Avg. time of first trade/period	Avg. time transactions take place
Periods 1 to 8	0.93	3.91	4.20	10.5	55.5
Periods 9 to 16	0.49	3.44	4.01	11.3	55.5
Periods 17 to 24	0.35	3.46	4.23	10.0	54.1
p-value	0.00	0.04	0.95	0.96	0.22

T3	Standard deviation of prices/period	number of transactions per trader per period	Avg. volume per transaction	Avg. time of first trade/period	Avg. time transactions take place
Periods 1 to 8	1.11	4.00	3.61	15.7	58.0
Periods 9 to 16	1.01	3.79	3.81	18.8	60.9
Periods 17 to 24	0.87	3.88	3.91	22.7	60.8
p-value	0.12	0.88	0.16	0.06	0.34

In all three treatments prices become more stable over time – most likely because traders become more experienced and more careful in their trading activities. This should be reflected in the data as well, e.g. by fewer transactions, fewer stocks exchanged per transaction, and later trading within each period, as participants wait for better offers. The second column of table 4 presents the number of transactions per trader and period over time. We see that this number decreases significantly in the first two treatments but only slightly in T3. In the third column we see the average number of stocks exchanged in each transaction, but the changes are not significant in any treatment. The same can be said for the time it takes until the first transaction takes place. In a last analysis we examined whether transactions took place later within each period over time. However, the last column of table 4 shows that this is not the case, as average trading time within each period stays essentially the same in all three treatments.

Above we outlined that in REE only traders with *I5* should trade and consequently prices would reflect their, i.e. all available information. However, if only 'naïve trading' took place, prices should rather reflect the information level of *I3*, i.e. prices should move two periods after changes in the fundamental value. To test which model describes our experimental results better we computed the Pearson correlation between the development of average prices per period and the development of fundamental values (CPV of *I5*) lagged by zero (*I5*) to four (*I1*) periods. In addition we calculated the Pearson correlation between the median of the five CPVs (=third highest CPV) in each period and the respective average price. The numbers for each information level for all five (in T1 and T2) or six (in T3) markets were then Fisher z-transformed to allow for the computation of averages. These average correlation coefficients are presented in the table below.

Table 5: Pearson correlation (Fisher z-transformed) between average prices per period and conditional present values of I1 to I5 and between average prices and median CPV

	I1	I2	I3	I4	I5	Median CPV
Treatment 1	0.81	0.92	**0.94**	0.90	0.75	**0.97**
Treatment 2	0.61	0.75	**0.82**	0.79	0.65	**0.85**
Treatment 3	0.64	0.71	**0.74**	0.66	0.44	**0.84**

We see that the development of prices lags behind the development of the fundamental value provided to *I5* by two periods in all three treatments. This means prices reflect only the information available to *I3*.[11] Clearly REE does not hold and our markets are not strong-form efficient in the sense that "*all available information is reflected in prices*" (Fama 1970). For this to hold prices would have to correlate highest with *I5*'s information.

When defining 'naïve trading', we suggested that prices would closely reflect the median trader's expectation (i.e. the CPV of the information level with the third-highest estimate in a period) if traders would trade "naïvely". To test whether this holds true for our markets, we computed the Pearson correlation between average prices per period and the median CPV of the five traders. We took the median CPV for every period and correlated the development of this series with the development of average prices. The respective numbers are presented in the last column of table 5. We consider it remarkable that these coefficients are higher than any correlation for any individual information level in all three treatments. Once more the predictions of 'naïve trading' hold well.

To conclude: prices in our markets lag behind the insider's knowledge by two periods. Prices do not reflect all available (i.e. also insider) information, but only about the average information in the market.[12] This means that information that is known to the majority of traders (three of five information levels) is reflected, while insider information is not. As information known to the majority can be considered 'public information' our markets can be considered 'semi-strong form efficient' in the sense of Fama (1970). Obviously there is no 'learning from the best', but market prices reflect averages of trader's diverging opinions as can be expected when traders follow 'naïve trading'.

When we look at the absolute level of prices as compared to fundamentals we find that prices are on average slightly higher than the median CPV in T1 and T2. Specifically they are on average 7.3 percent higher than the median CPV in T1 and 6.9 percent higher in T2. In T3,

[11] When we look at individual market data correlation with I3 is highest of the five information levels in four of five markets in T1 and T2, and in four of six markets in T3.

[12] Kyle (1989) found a similar result in a very different market setting.

where short selling was allowed, average prices in five of the six markets reflected median CPV very well, while only M6 showed higher than justified prices. Overall prices were 2.2 percent higher than the respective median CPVs in T3. This suggests that short selling constraints and the different incentive structure in T1 and T2 have most likely had an impact on overall price levels. This will be examined next.

5.5 Short selling constraints

In T1 and T2 going short in cash or stocks was not allowed. This may explain why we see a slight overvaluation these two treatments, as several papers suggest that short selling constraints may lead to higher prices or even bubbles (e.g. Duffie et al. 2002, Shleifer/Vishny 1997). Probably the limitations on short sales also cause prices not to reflect all available information, as called for in an efficient market. T3 was conducted to shed some light on these issues. We found that the overvaluation is indeed almost non-existent in T3. However, prices still lag two periods behind the insider's fundamental information and are best proxied by the median CPV in all three treatments.

In this chapter we present some data on how often traders in T1 and T2 were possibly constrained by the limitations on short stocks or cash, and how often traders did go short in T3. In T1 and T2 we consider a trader potentially constrained if more than 95 percent of his total wealth is held in cash or in stock. We summed the cases up for each period, each trader, and each market. However, we exclude from the analysis data from several traders who sold all their shares in the first few periods and then were (almost) inactive for the remainder of the experiment.[13] Across all markets and all information levels in T1 we find that in 4.89 percent of all cases traders held 95 percent or more of their total wealth in stock. The respective

[13] We did not consider the data of eight traders in T1 and ten traders in T2 for this analysis. The traders were spread across all markets and all five information levels.

number for 95 percent or more in cash is 5.28 percent in T1. In T2 the numbers are 2.81 percent of all cases for stocks and 4.73 percent for cash.

While we do not know whether the respective traders would have been ready to go short in stock (exposing themselves to substantial risk) when fully invested in cash, or take a loan to increase their stock position when cash is constrained, the constraints might have played a substantial role in the pricing process, especially when the best informed traders were constrained and prices therefore cannot reflect their private information. When we look at the information level of the constrained traders we see that in T1 the best informed *I5* are among the constrained traders most often, except for *I3*. However, the difference between *I5* and all others is not significant (two-sided Mann Whitney U-test, p=0.408). In T2 we do not find any significant differences as well. This can be seen in table 6 where we present data showing how often (percentage of all periods) traders of each information level had more than 95 percent of their total wealth in cash or stock.

Table 6: Percentage of cases per information level when traders held more than 95 percent of their total wealth in money or stocks in T1 (left) and T2 (right)

T1	cash>95%	stock>95%	Total
I1	3.74%	3.54%	7.28%
I2	2.40%	4.36%	6.75%
I3	6.30%	7.61%	13.91%
I4	2.56%	7.09%	9.65%
I5	11.39%	1.86%	13.25%
Total	5.28%	4.89%	10.17%

T2	cash>95%	stock>95%	Total
I1	2.90%	3.31%	6.21%
I2	5.04%	1.75%	6.80%
I3	6.11%	1.97%	8.08%
I4	3.92%	4.61%	8.53%
I5	5.68%	2.40%	8.08%
Total	4.73%	2.81%	7.54%

The best way to clarify whether these constraints have a major impact on the market is to lift them. We did so in treatment 3 where traders could go short in money and stocks without limitations and without incurring any extra costs. First we counted to what percentage of all periods each trader did go short in money or stocks. The respective numbers (6.28 percent short in money and 4.27 percent short in stocks) are comparable to what we found for T1 and T2 (see table 6). When looking at individual information levels we find *I5* to make significantly more use of short selling possibilities than information levels *I1* to *I3* (Mann-Whitney U-test, p=0.029). Usually traders used short sales cautiously, going short no more than 25 percent of their initial endowment of stocks or money.

Table 7: Percentage of cases per information level when traders were short in money or stocks in T3

T3	short money	short stock	Total
I1	2.95%	5.90%	8.85%
I2	1.91%	3.99%	5.90%
I3	5.03%	1.04%	6.08%
I4	6.60%	5.38%	11.98%
I5	14.93%	5.03%	19.97%
Total	6.28%	4.27%	10.56%

However, in M4 three traders (one each with information levels *I1*, *I3*, and *I5*) did go short by more than 100 percent of their initial endowment for at least one period, resulting in extreme returns (negative for *I1* and *I3*, positive for *I5*[14]). The overall distribution of returns in T3 is also wider than in T1 and T2, as can be seen in figure 3. One consequence of short selling constraints might be that the insider's ability to trade on their information may be hampered, resulting in prices that do not reflect insider information, as seen in T1 and T2. However, with short selling constraints completely lifted in T3 we still see prices lagging behind the insider's CPV by two periods in T3 (see table 5).

One possible explanation for this is that insiders consciously choose not to reveal their information by accepting limit orders by other traders rather than posting limit orders themselves. This is supported by the experimental data: usually 62 percent of transactions involving insiders (*I5*) result from limit orders posted by them, but when they are short in either money or stock the respective number is only 41 percent. This means that they

[14] At the end of the session *I1* had lost 46 percent relative to the market average. *I3* lost 75 percent, while *I5* had a net profit of 78 percent.

predominantly accept limit orders posted by other, worse informed, traders, thereby avoiding to reveal their information.

However, allowing short sales has one marked influence on prices: the slight overvaluation observed in T1 and T2 (by about 7 percent each) disappears completely in five of the six markets in T3. Only in M6 with a very negative development of fundamental values do prices not follow suite immediately, resulting in prices being markedly higher than justified by fundamental values. However, by the end of the session the over-valuation disappears in this market as well. We cannot say for sure whether this difference to the first two treatments, where we observe some over-valuation, was caused only by the possibility to go short in money and stocks, or whether the changed incentive structure also played a role.

6 Conclusion

In this paper we presented results from several experimental financial markets with asymmetrically informed traders. Our goal was to examine how information is processed in a market and how it influenced the distribution of net returns. In all three treatments we conducted we find a "J"-shaped distribution of returns across information levels: while the best informed can outperform the market, all others can not. Among the group of non-insiders we find that the average informed *I2* and *I3* fare significantly worse than the least informed *I1*.

While REE would result in very low trading activity with prices reflecting all available information, we find very active trading at prices which mostly reflect the fundamental information of the median trader in each period. This result differs from earlier studies, where REE was found to be quite accurate (e.g. Plott/Sunder 1988 and Sunder 1992). However, our second proposed benchmark, the 'naïve traders' describes the results of our experimental markets quite accurately. We find our results to be robust to changes in design features like allowing/forbidding short sales, changing the incentive structure, and changing the way information is presented.

We consider the “J”-shaped return distribution the most important finding, as we think it allows to shed some light on the empirical evidence Cowles (1933, 1944), Jensen (1965), Malkiel (2003a, 2003b) and many others have gathered. Their studies show that the majority of actively managed funds and professional stock market forecasters perform worse than the broad market. These people undoubtedly process huge amounts of information, but they are not insiders, so they would probably have information level *I3* in our experiment. We think the impressive growth of index funds since their introduction in the early 1970ies can be interpreted as a rational reaction by market participants if they find that they cannot beat the market by trading on information. Probably investors become more experienced, possibly also more willing to accept earning the market return instead of a promise – often unfulfilled – of earning more. William Fouse, who initiated the emission of the first index fund in 1970, warned about the “*quicksand premise that increasing knowledge about a company guarantees greater forecasting success*” (in Bernstein 1992, 245). In the early 1990ies about one-third of institutional money was already invested in index funds (Bernstein, 1992). Bogle (1999) reports that in 1995 about 40 percent of all funds were invested in index instruments. In addition Cremers and Petajisto (2006) report a ‘silent indexation’ of actively managed mutual funds: while twenty years ago 99 percent of funds had 60 or more percent of their assets under active management the respective share dropped to less than 60 percent of funds in 2003. One out of eight of ‘actively managed’ funds actually has less than 20 percent of his assets under active management while the largest part is invested in the index.

In earlier papers (Huber et al. 2006a, 2006b) we showed that information is not necessarily useful in markets. In these papers we argued that this is mainly due to the fact that the worst informed have very little information to process and therefore trade almost randomly, yielding the market average return. In this paper we present another line on argumentation, as we link the relatively good performance of the worst informed to the development of prices in a market. During trends more information is generally useful, while during trend reversals the average informed will perform worst. This implies that more information does not necessarily improve a trader's expected return in a market.

While our results are robust to several design changes a number of limitations of this study should be mentioned – some of them cover questions for future research.

The information structure we chose for all three treatments is a cumulative information system, meaning that all traders have eventually access to the same information, but better informed traders get it earlier. We chose this approach as we agree with Figlewski (1982, p.99) that "*an independent information is not likely to be an adequate description of the information structure of a real-world speculative market*".

In our experiments the information level was randomly assigned to participants at no cost. However, in real markets traders chose actively how much to spend on information gathering. An endogenous selection of the information level, as first implemented by Sunder (1992) should be one of the focuses for future research.

On short selling we did the two most extreme cases – completely forbid in T1 and T2 and unlimited in T3. Several settings in between would be possible, e.g. allowing short sales but only up to a certain amount, or allowing it only to insiders but not to others. In addition going short could be allowed but only at some extra cost.

Finally, all our markets were conducted with traders starting with equal endowments of money and stock and an equal number of traders per information level. A more realistic setting would be to have a few well endowed insiders and an increasing number of traders with lower starting endowments as the information level becomes lower.

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Appendix A

Written Instructions for treatment T1

Dear Participant! We welcome you to this experimental session and kindly ask you to refrain from talking to each other for the duration of the experiment.

Background of the experiment

This experiment is concerned with replicating an asset market where traders can trade the stocks of a fictitious company for *k* consecutive periods (quarters of a year).

Characteristics of the market

Each trader is initially endowed with 1600 talers (experimental currency) and 40 stocks. The only fundamental information you receive is the dividend of the stock (quarterly dividend equals quarterly profit of the company) which follows a random walk process without drift:

$$D_k = D_{k-1} + \varepsilon$$

D_k denotes the dividend of period k and ε represents a normally distributed random variable with an expected value of zero and a standard deviation of 15 percent. This period's dividend is therefore the best estimate for next period's dividend. The market is characterized by asymmetric information. The worst informed trader knows only the dividend of the current period, while better informed traders can estimate the dividends of the companies a few periods into the future. At the end of each period (after 100 seconds), you will receive the current dividend for each stock you own. A risk-free interest rate of 0.5% is paid for the cash holdings in each period. The risk-adjusted interest rate for valuation of the stock equals to 2.0% per period.

Calculation of the conditional expected value (present value, PV)

It is up to you to decide how to trade and how you evaluate the stock. If you want to use your fundamental information (expected future dividends) you can see the present value (PV) of all future dividends (of course only those you can estimate on the basis of your information level) on the bottom left side of the trading screen. Your PV is derived using Gordon's well-known formula, discounting the dividends you know with the risk-adjusted interest rate of 2.0% and assuming the last one as a continuous, infinite stream which is also discounted. If you follow this information, it makes sense to buy at a price that is lower than your PV and sell at a price that is higher than your PV.

$$BW_k = \sum_{k=0}^{n-1} \frac{D_k}{1.02^k} + \frac{\frac{D_n}{0.02}}{1.02^{n-1}} \qquad n \text{ indicates the 'last' dividend you know}$$

Example: The dividends of this (k=0) and the next two periods are 0.791; 0.814; 0.802. The PV on the basis of this information level is calculated as follows: 0.791 + 0.814/1.02 + 0.802/0.02/1.02^2 = 40.23. This PV on the basis of your information level is shown on the bottom left side of the trading screen.

Trading

The trading mechanism is implemented as a double auction. This means that each trader can buy and sell stocks. You can enter as many bids and asks within the price range of 0 and 200 (with a precision of one decimal place) as you wish. Additionally, you have to insert the quantity you want to trade (1 to 10 shares). A new offer to buy is only accepted if the sum of this and all your outstanding offers to buy (price multiplied by the corresponding quantity) is not higher than your current cash holding. Otherwise a message box appears to inform you that the offer is not valid. This check is made to prevent your cash holdings from dropping below zero. A new offer to sell will be accepted if the sum of that offer and all your outstanding offers to sell is lower than your current stock holding. Otherwise a message box appears. This check is made to prevent your stock holdings from dropping below zero.

Example: Your current cash holdings equal 600 talers. Your outstanding offers to buy equal 532.5 talers, containing one offer of 10 stocks at a price of 35 talers and another offer of 5 stocks at a price of 36.5 talers. In this case, the product (price times number of shares) of your new offer to buy (price multiplied by number of stocks) must not exceed 67.5 talers.

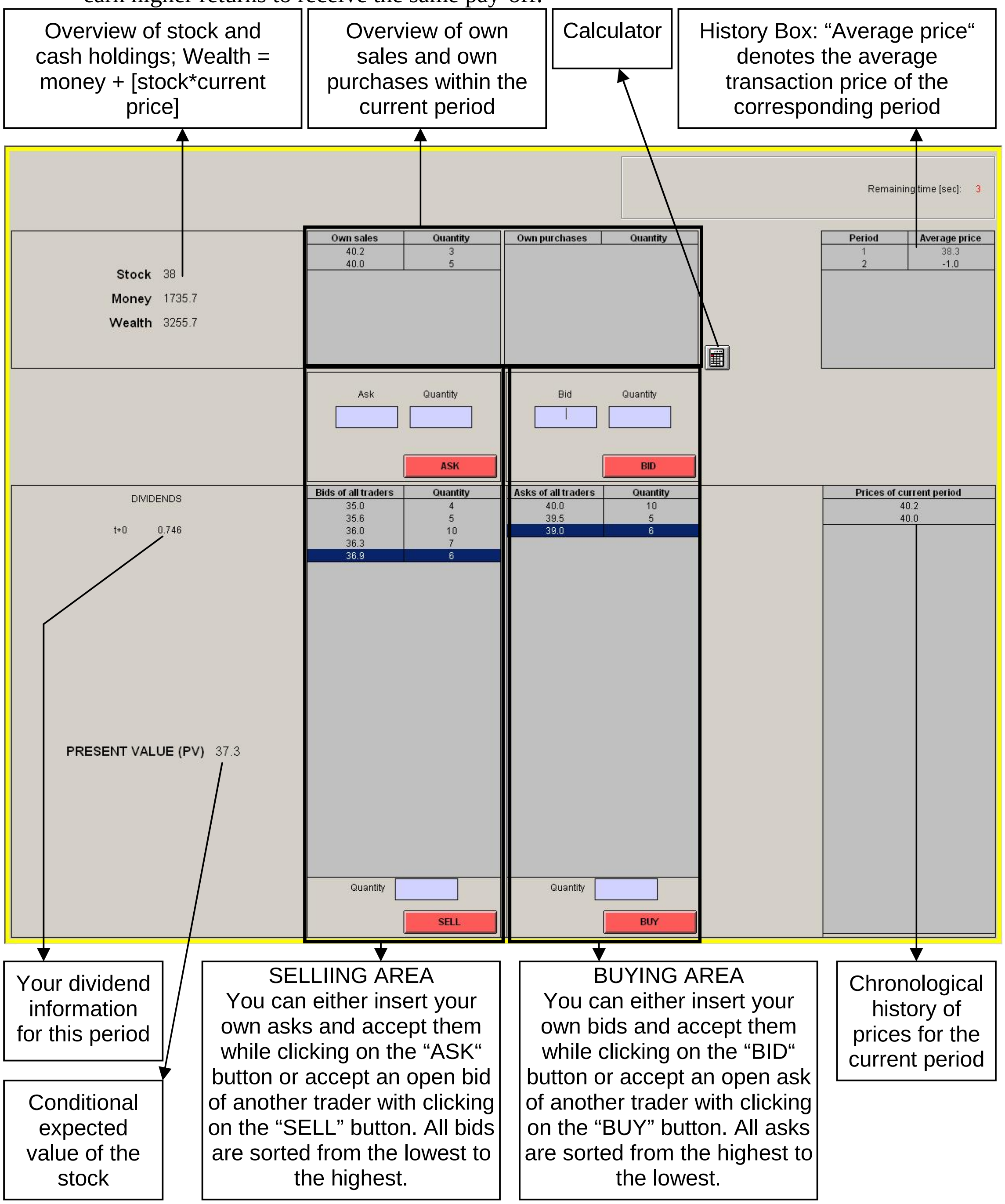
Wealth

Your wealth is the sum of your cash holding and the total number of the stocks you hold multiplied by the current price. If you buy a stock, your cash holdings decrease, and at the same time your stock position increases by the quantity you traded. Generally, the current price on the stock (marking-to-market) is used to evaluate your wealth, so your wealth will change even if you have not participated

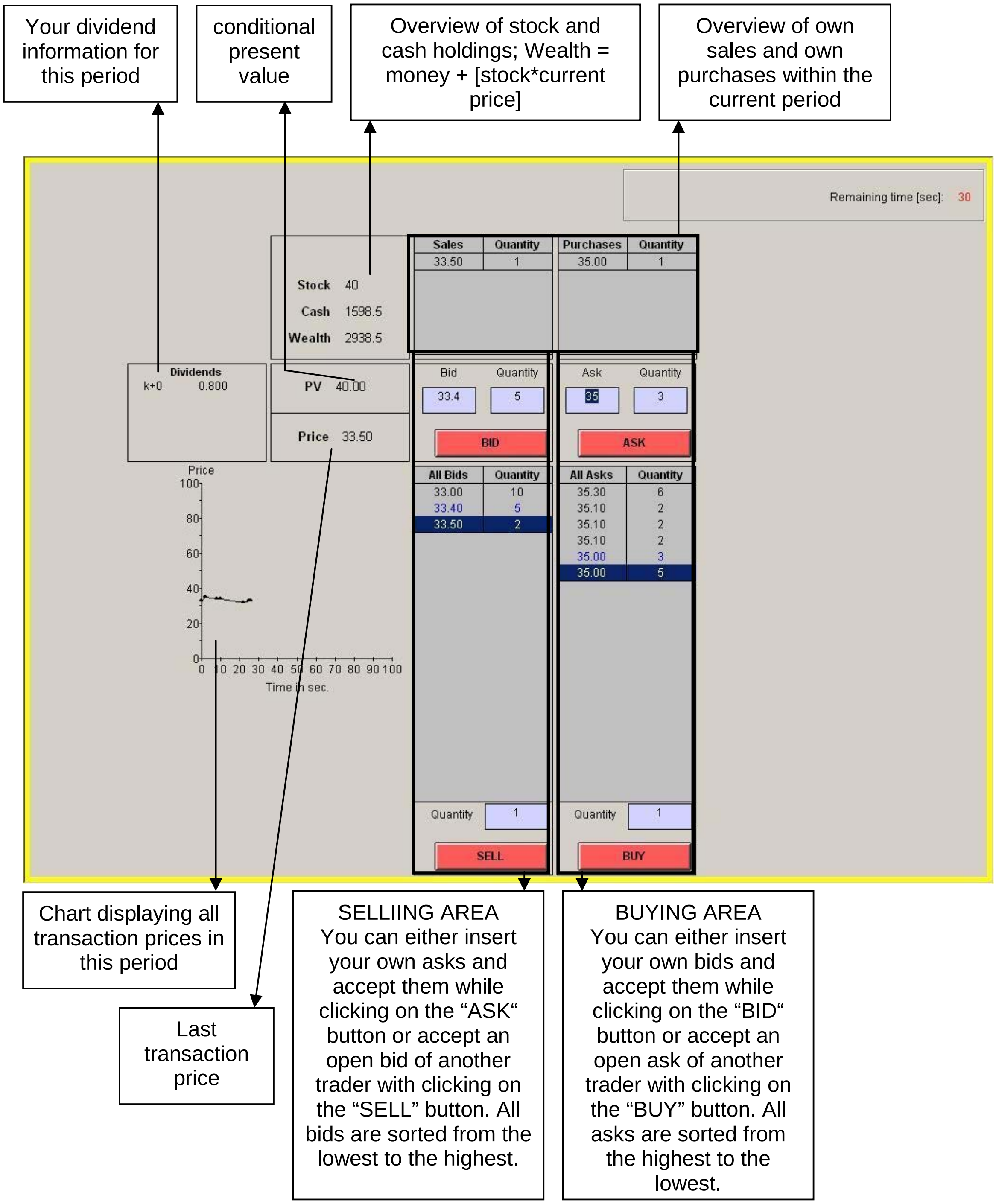
in the last transaction. At the end of each trading period, you receive an interest rate of 0.5% per quarter on your current cash holdings, and the dividends for your stocks are added to your cash.
Example: If you own 1600 in cash and 35 stocks with a price of 50 that pays a dividend of 0.815 at the end of a period, your wealth increases from 3350 to 3386.53 (+8.0 interest earnings (1600x0.005), +28.53 dividend earnings (35x0.815)).

Important details

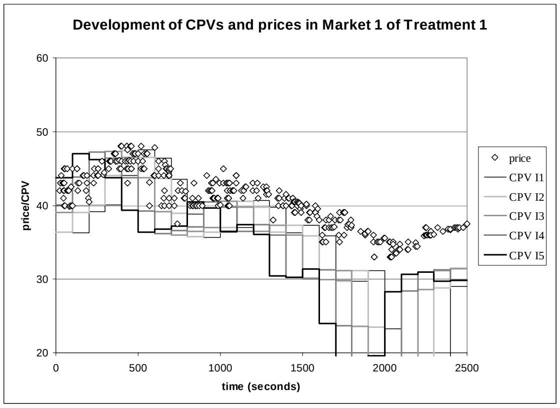
- The experiment will be randomly terminated between period 20 and 30, with equal probability for each period.
- Your pay-off at the end of the experiment depends on your relative performance in the market. This means that your wealth at the end of each period will be compared with the average wealth in the market at the same time. This relation is summed up across all periods. Your pay-off will be above average if you can manage to 'outperform' the market. Note that your pay-off will be calibrated according to your information level, e.g. the best informed have to earn higher returns to receive the same pay-off.

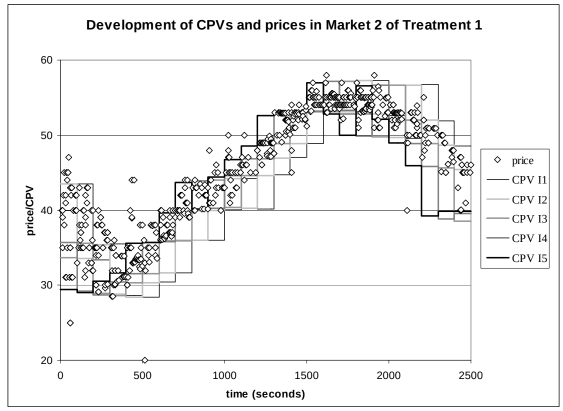


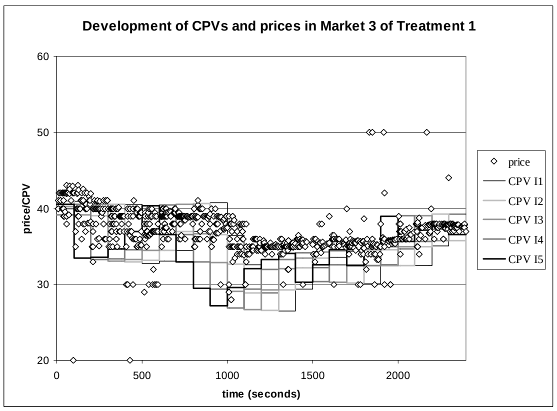
Trading screen of Treatment 2

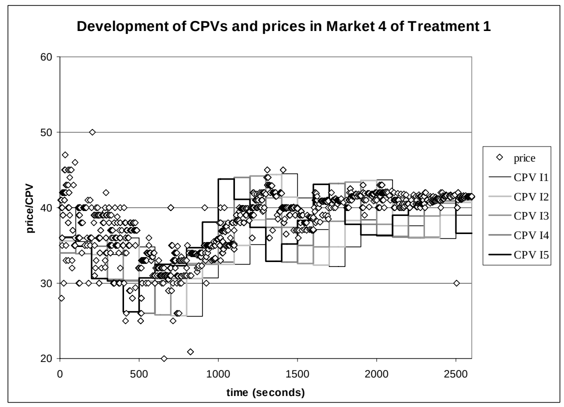


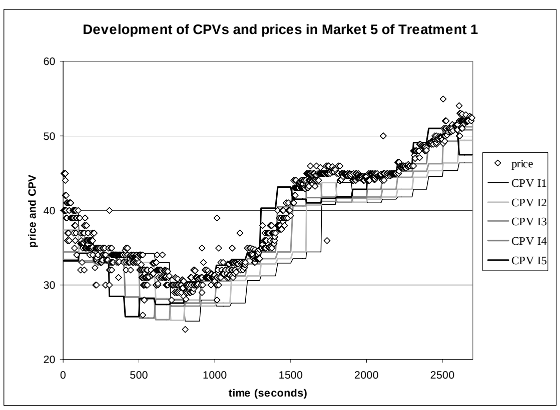
Appendix B: Plots of conditional present values (CPVs) and prices in Treatment 1



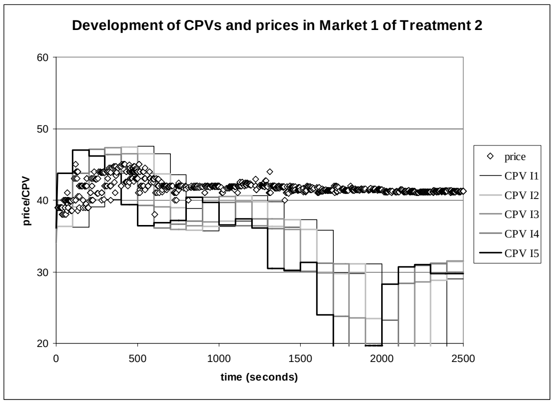


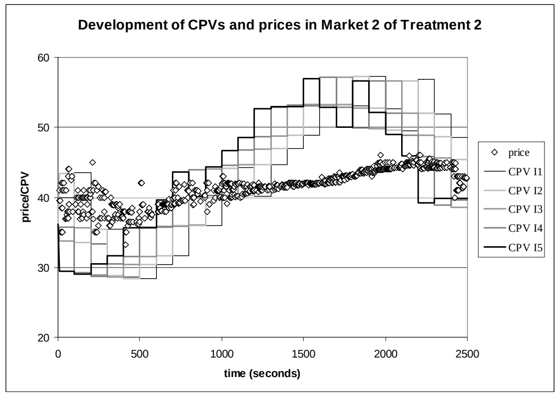


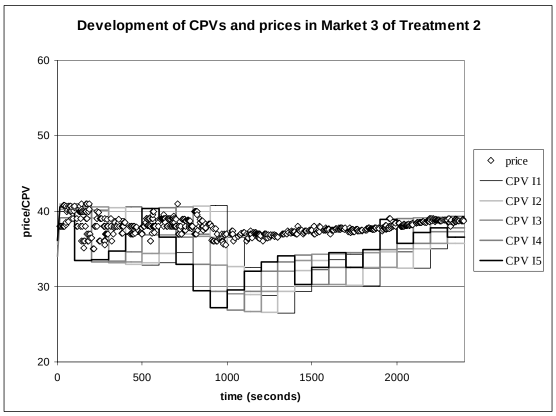


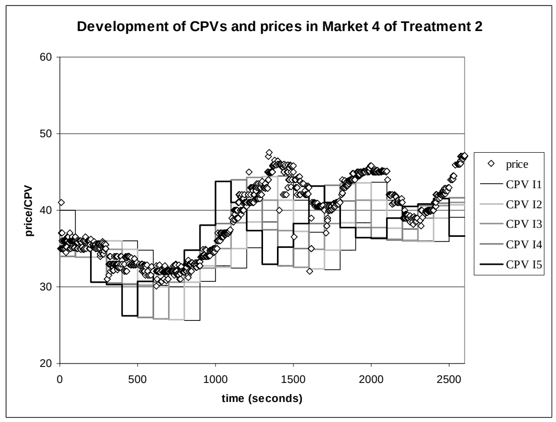


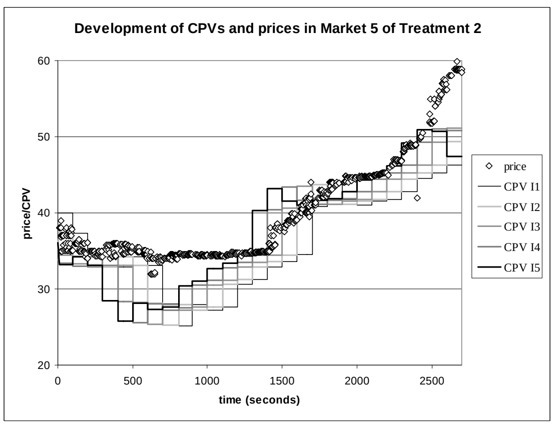
Plots of conditional present values (CPVs) and prices in Treatment 2











Plots of conditional present values (CPVs) and prices in Treatment 3